C-5M FUEL EFFICIENCY THROUGH MFOQA DATA ANALYSIS

THESIS

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Abstract

This study investigates the usage of Military Flight Operations Quality Assurance (MFOQA) data as a means to obtain precise, aircraft-specific fuel loads. Currently, USAF C-5M aircraft include a 4% “degrade” value in their fueling practices. MFOQA data are analyzed in an attempt to refine this value. Case study data are analyzed from a single C-5M. A model is constructed using smoothing techniques which compare MFOQA actual observations to a baseline flight test model. The resulting figures are applicable to fuel planning and fuel efficiency concepts. Validation is presented through comparison with computerized flight planning software output. Results from the case study analysis are presented within the framework of fleet-wide implementation and maintenance practices.

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Michael P. Mariotti

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I. Introduction

The United States Air Force (USAF) operates an enormous fleet of aircraft. Within the USAF structure, Air Mobility Command (AMC) operates a fleet of large transport aircraft designed for heavy airlift missions. These so-called "heavies" consume large amounts of aviation fuel. Rising fuel costs combined with austere fiscal conditions are a significant challenge for AMC airlift operations. Efforts to reduce AMC fuel consumption while maintaining mission effectiveness are of utmost concern for the command.

Given that AMC consumed roughly 63% of all the fuel used in the entire USAF in 2011 (and therefore a large portion of the DoD fuel usage), ongoing efforts aimed at improving fuel efficiency resulted in many changes to policies and procedures at AMC (United States Department of Energy, 2012). Fleet-wide fuel consumption and fuel efficiency is a complex problem which requires investigation into both the aircraft systems and the fleet's operational procedures (Lee et al., 2004). Instituting standardized fleet-wide policies regarding fuel usage is critical not only for cost savings but also for addressing environmental concerns (Lee, 2010). Reiman (2014) notes the importance of a holistic enterprise approach to fuel efficiency. The concept of fuel efficiency regarding a fleet of aircraft requires analysis of a dizzying array of factors: fuel loading, cargo loading, routing, flight duration, etc. Quantifying the various aspects contributing to fleet fuel efficiency is not an easy task. Despite the challenges, there is a vast body of research indicating that proper data analysis can contribute to improved fuel efficiency in a fleet of aircraft.

This study focuses on a very specific aspect of fuel efficiency: engine fuel consumption at cruise. Properly quantifying the actual fuel burn of each individual engine permits flight planners to calculate a more precise fuel load for a specific aircraft on a specific mission. It is a deceptively complex question: How much fuel goes on an aircraft to complete a mission? The answer to this question is critical. Excess fuel leads to costly waste while a shortage could result in a costly diversion to an alternate destination. An optimal "ramp" fuel load is critical since any excess fuel acts as "cargo". In other words, any surplus fuel beyond that needed to safely complete the mission simply increases the gross weight of the aircraft and decreases the overall fuel efficiency for the flight. AMC publications estimate a loss of 3% per hour per pound of excess fuel loaded. For example: 1,500 lbs of fuel is burned during a 5 hour flight to accommodate an extra 10,000 lbs of fuel (AMC Pamphlet 11-3, 2007). Reiman et al. (2011) suggest the use of a fueling accuracy metric to quantify this phenomenon and ensure no excess fuel is loaded. Clearly, optimizing ramp fuel loads is critical to the efficient operation of an aircraft fleet.

Inherent to the concept of an optimized ramp fuel load is an engine-specific (and therefore aircraft-specific) measurement of fuel burn. The atmospheric and mechanical factors affecting fuel burn rate in jet engines are well researched and understood. It is also well understood that aircraft engines deteriorate over time and associated variation in the fuel burn rates of individual engines can be drastic (Mehalic & Ziemianski, 1980).

Observing, estimating, quantifying, and updating fuel burn rates for individual engines can be both time consuming and labor intensive. In practice, a blanket "fuel bias" or "fuel degrade" is often applied to account for deterioration and other factors (Srivastava et al., 2012). These biases are incorporated into flight planning software to produce ramp fuel loads. Indeed, AMC produces computer flight plans for their aircrews which add "fuel degrade" values to help ensure a proper amount of fuel is placed on the aircraft. Analysis of available datasets may contribute to refined degrade values. Refined values would then contribute to more accurate fuel loading and more efficient fleet fuel usage.

Flight Operations Quality Assurance (FOQA) data uses the quick access (QAR) data from aircraft flight recorders (the so-called "black box"). FOQA records data on a wide array of flight parameters for a particular flight (Lowe, Pfleiderer, & Chidester, 2012). Airlines, through coordination with the Federal Aviation Administration (FAA), have analyzed FOQA data for decades. The FAA-sponsored FOQA program's stated goal is risk mitigation through the identification of unsafe trends in operation. More recently, the usefulness of FOQA has been demonstrated for maintenance and health monitoring of the aircraft systems (Stolzer, 2002). Insights gleaned from FOQA analysis is even beginning to gain a foothold amongst military aircrews as a training tool (Haas et al., 2008).

Recognizing the safety and operational benefits of FOQA, the Office of the Secretary of Defense (OSD) issued a policy memo in 2005 directing a Military Flight Operations Quality Assurance (MFOQA) process implementation. The USAF responded in kind with Air Force Policy Directive 90-13, "Military Flight Operations Quality

Assurance". Although gathered, analyzed, and maintained mostly for safety and readiness issues, AFPD 90-13 acknowledges the potential for "enhanced maintenance operations". Stolzer (2003) outlines how this is possible:

> Typically, modern digital aircraft capture and store between 200 and 500 parameters per second…including gauge readings, switch positions, control wheel deflections, control positions, engine performance, hydraulic and electrical system status, and many others (p. 6).

In other words, MFOQA records almost everything of interest going on with the aircraft. Although massive and unwieldy, the raw MFOQA represents a gold mine of aircraft data. Within the framework of fuel efficiency and aircraft-specific fuel burn rates, MFOQA data has great analysis potential.

The USAF C-5M "Super Galaxy" is the latest modification to AMC's C-5 cargo aircraft. The C-5 is the largest aircraft in the USAF fleet and performs a wide array of airlift missions across the globe. AMC records indicate the C-5 fleet flew well over 30,000 hours in both fiscal year 2011 and 2012 (Air Mobility Command, 2014). AMC's Tanker/Airlift Control Center (TACC) at Scott Air Force Base produces most of the optimized flight plans for C-5M crews. These flight plans include ramp fuel loads calculated with computer flight planning software in a process similar to most airline dispatch centers. These flight plans are optimized for various input parameters: sortie type, duration, cargo, weather, etc. The flight planning software also plans the fuel load based on the technical order data provided to the USAF by Lockheed (the aerospace corporation that builds the C-5M). Currently, AMC flight planners add a 4% fuel degrade to the baseline fuel burn quantities when calculating the ramp fuel loads for the C-5M aircraft. This 4% "pad" accounts for the variation in engine performance discussed earlier. Proper examination of the available MFOQA could contribute to a more refined degrade quantity for an individual C-5M.

This study determines if MFOQA gathered from the C-5M is a viable method of quantifying a highly accurate fuel degrade figure for an individual aircraft. Recall that any extra fuel (even if added as part of the 4% "pad") acts as cargo and decreases the overall fuel efficiency of a given sortie. Consider, for instance, if the burn rate on a particular C-5M is more accurately described at 3.9% instead of 4% from the baseline technical order fuel burn rate. On long haul missions, the C-5M carries roughly 160,000 lbs of jet fuel for an 8 hour flight (Lockheed Martin, 2012). In this case, the revised padding factor reduces the ramp fuel load by 160 lbs (one tenth of one percent). This may seem to be a "drop in the bucket", but consider that a C-5M easily flies several hundred such missions in a year (C-5 aircraft logged over 30,000 hours in FY 11) (Air Mobility Command, 2014). Also, based on the "3% rule" outlined above, the C-5M burns another estimated 38.4 lbs of fuel to accommodate the 160 lbs of excess ramp fuel. AMC estimates a cost of $3.79 per gallon of fuel in FY12 (Air Mobility Command, 2014). A baseline density for military grade JP-8 fuel is 6.8 lbs per gallon (Lockheed Martin, 2012). With these figures, an estimated cost for 198.4 lbs of wasted fuel is roughly $110. The carrying costs alone constitute approximately $21 of the $110.

The figures compound quickly for an entire fleet over a year of operations. AMC databases show C-5 aircraft flew roughly 16,000 hours in FY 12. Given this information, a mere one tenth of one percent translates into roughly $200,000 in overall fuel costs. The carrying costs alone constitute $42,000. The $42,000 could be considered an immediate cost savings, whereas the overall cost of $200,000 represents an inventory reallocation. Consider also the cost of underestimating the degrade value. Suppose an engine is over-consuming fuel at a rate of 5-6% degrade instead of the advertised 4%. In this case, fuel conservation practices leading to razor thin fuel reserve margins could cause inadvertent and costly diversions and mission delays. Accurately quantifying the fuel degrade figure for an individual aircraft has massive fuel and cost savings potential. Chapter I framed the overall scope of this thesis: exploring the use of MFOQA to provide refined fuel degrade values for the C-5M aircraft. Chapter II will provide further details on the project by outlining the applicable literature surrounding the subject.

II. Literature Review

Chapter Overview

As discussed in Chapter I, FOQA lends itself to in-depth data analysis due to the wealth of information contained in the data. Research into the use of FOQA for aircraft engine diagnostics emerged in the last decade as a natural extension of the quality control and safety monitoring originally intended for the FOQA program. A subset of this research surrounds fuel efficiency through FOQA analysis.

To understand the current state of research in the realm of FOQA analysis on fuel efficiency, a host of online research databases, article repositories, conference proceedings, scholarly texts, and online search engines were examined. Keywords in the searches included "FOQA", "Fuel Efficiency", "Fuel Consumption", "Aircraft Fleet", "Data Analysis", "Data Mining", and others. Various combinations of the above keywords yielded many of the same sources suggesting these to be the more seminal works on the subject.

Figure 1 is representative of the body of work surrounding FOQA and fuel efficiency. The literature is broken down by subtopics which will be discussed in this chapter.

Related Works	Fleet Health Monitoring	FOQA/QAR Data Analysis	Engine Diagonsitc Tools	Fuel Consumption	Filtering/Smoothing/Estimation	Advanced Techniques	Anomaly Detection
Babikian et al (2002)	•			•			
Chang (2014)			•			•	•
Chu et al (2011)	•					•	•
Chu et al (2010)		•				•	•
Cleveland (1979)					•		
Collins (1982)				•			
Garbi (2007)				•			
Grewal and Andrews (2008)					•		
Gorinevsky et al (2012)		•				•	•
Kalman (1960)					•		
Kobayashi and Simon (2003)			•		•		
Kobayashi and Simon (2004)			•		•		
Kobayashi and Simon (2005)			•			•	
Kwan et al (2014)	•			•			
Li (2010)		•		•	•	•	
Li et al (2011)		•				•	•
Lockheed Martin (2014)	•	•		•	•		
Mehalic and Ziemianski (1980)	•		•				
Monnin et al (2011)	•			•		•	
Schilling (1997)				•		•	
Simon (2008)			•		•		
Simon and Simon (2010)			•		•		
Simon and Garg (2010)			•		•		
Simon and Armstrong (2013)			•		•		
Srivastava et al (2012)	•	•		•		•	•
Staszewski et al (2004)	•				•		
Stolzer (2003)	•	•		•			•
Stolzer and Halford (2007)	•	•		•		•	•
Torenbeek (1997)				•			
Woodbury and Srivastava (2012)	•	•		•		•	•

Figure 1 - Relevant Sources

Fleet Health Monitoring

Examining a complex concept such as fuel efficiency begins by examining the fleet as a whole. The engineering effects within the fleet are the most straightforward. The fact that older engines are less fuel efficient is well known. Quantifying such effects is vital to fleet fuel efficiency. Serious research into the degradation of aircraft engines in terms of fuel efficiency has gone on for decades (Mehalic and Ziemanski, 1980). As technology improved, researchers explored both the physical factors as well as the operational policies that influenced fuel burn rates in aircraft fleets (Babikan et al., 2002). These practices gave rise to the concept of fleet health monitoring.

The main purpose of this thesis is utilizing FOQA to learn about the fuel consumption behavior of individual aircraft. Specifically for the C-5M, the goal is to obtain precise, aircraft-specific fuel loads through the application of a precise fuel degrade figure. This process can be seen as very specific form of fleet health monitoring. Monnin et al. (2011) underscore the importance of fleet-wide health monitoring. They offer several models which demonstrate the synergistic effects arising from analysis of individual units within the operations framework of the entire fleet. Kwan et al. (2014) provide a report for the international council on clean transportation by ranking major U.S. airlines using a “fuel efficiency” score gleaned from various fleet-wide policies and procedures implemented by the companies. Aircraft-specific fuel loading (the tailored “ramp” loads described in Chapter I) is one of a myriad of considerations accounting for the overall fuel efficiency score. Several studies examine FOQA and other data sources for fuel burn rates and other fleet health information. For example, Chu et al. (2011)

describe adaptable and scalable models within the framework of statistical process control. The intended use of these models is overall fleet health monitoring (not just fuel efficiency). Stolzer (2003) and several others listed in Figure 1 focus specifically on fuel efficiency but their work is aimed at fleet-wide monitoring and implementation. These trends in the research clearly suggest that FOQA analysis is rarely, if ever, conducted in a vacuum. Researchers are considering the fleet-wide ramifications of the outcomes of their studies.

FOQA/QAR Data Analysis

FOQA fits nicely into the fleet health monitoring framework and works well for many different forms of analysis. There are several reasons for this. First, it is collected regularly per both FAA and USAF policy as described in Chapter I. It is an existing data source that requires no additional resources to produce (Stolzer, 2003). The raw FOQA is readily available; however, manipulating the raw FOQA does require effort and skill. Another reason FOQA is so useful is the massive amount of information it contains. FOQA captures the entire flight envelope and almost any imaginable relevant parameter. This makes FOQA a very adaptable data source. For example, Chu et al. (2010) propose models for fleet-wide anomaly detection. They build the models by focusing upon a limited set of variables examined on the cruise portion of sampled FOQA flights. Stolzer (2003) and Stolzer and Halford (2007) also reduce the FOQA down to a very limited subset for their study on fuel consumption. Lockheed Martin (the aerospace company that manufactures the C-5M), conducted a study aimed at quantifying the specific range (cruise fuel burn) of individual aircraft. This study incorporated QAR-derived data similar to FOQA (Lockheed Martin, 2014). Li et al. (2011) utilize FOQA in a more traditional manner: they employ cluster analysis to identify anomalous flight parameters (airspeed, pitch, etc). Studies of this type abound. Gorinevsky et al. (2012) provide similar analyses to Li et al. (2011) by using FOQA for anomaly detection. Hailing from the NASA Ames Research Center, the authors propose various multivariate data reduction techniques to reduce terabytes of FOQA data to megabytes of scatter matrices. The implementation is through Hotelling T2 Statistics which are based upon empirical means and empirical covariances of the data. This is done within the framework of anomaly detection, but can be adapted to regression parameters. These studies demonstrate the wide applicability of FOQA to fleet health monitoring, but also illustrate the enormous and unwieldy nature of the data. Oftentimes a large portion of the research project goes toward data reduction or filtering. FOQA-derived research abounds despite its cumbersome nature.

Although data reduction is often applied to FOQA databases, they are also often used in their entirety. Srivastava et al. (2012) is another Ames Center study advocating the use of the entire dataset. Several exotic methods (ensemble regressions, bootstrap and kriging models, neural nets, etc) are applied to produce fuel consumption models. The goal is again anomaly detection, but specifically anomalous fuel consumption. This work was derived from a previous study (Srivastava, 2010) dealing with general linear models and Gaussian regression techniques to model anomalous fuel consumption. Woodbury and Srivastava (2012) summarize the previous works. The journal article focuses more upon comparing the regression models and introduces a time element. The basic concepts involve regression models built upon limited FOQA inputs and analysis of time series relationships. The approach is closely related to the methodology applied in Chapter III (although the underlying models differ). Finally, Li (2010) presents a broad overview of techniques useful in managing the entire FOQA dataset. He references work in the fields of machine learning and data mining. This harkens back to the Stolzer and Halford (2007) study that echoes the same praise for such techniques. Pulling FOQA (or any other data source) with the intention of identifying or estimating anomalous engine performance is only one possible application of this highly adaptable dataset. Overall, there is a clear trend toward utilizing FOQA for anomaly detection. There are precious few studies dealing with parameter estimation. It is worthwhile to examine non-FOQA based studies that provide engine health parameter estimation.

Engine Diagnostic Tools

Data-driven estimates of engine health parameters often begin with models of the internal processes of the engines themselves. For example, Kobayashi and Simon (2005) employ a nonlinear simulation of engine components for use in their analysis. A similar approach is taken in their previous studies, although the analysis techniques themselves differ (Neural Networks and Genetic Algorithms for the 2005 study versus Kalman Filter techniques for the previous studies). Simon (2008) offers a brief summary of algorithms proposed for engine health monitoring listing regressions, filtering, and smoothing techniques alongside other advanced techniques including neural networks, fuzzy logic, and genetic algorithms. Indeed, various researchers have applied each of these methods within various frameworks to produce estimable parameters. Taken as a whole, there is a wide array of available techniques to estimate engine health parameters. Kobayashi and Simon (2003), Kobayashi and Simon (2004), Simon (2008), Simon and Simon (2010), and Simon and Garg (2010) all build upon classical filtering techniques (Kalman, 1960) coupled with various associated optimization schemes within the filter to obtain results. Kobayashi and Simon (2005) utilize a neural network-genetic algorithm, and Chang (2014) approaches the problem with a fuzzy logic model. Clearly, there are many applicable algorithms employed in the problem of data analysis of engine health. For the scope of this thesis, it is prudent to examine a subset of engine health parameters – specifically fuel consumption.

Fuel Consumption

Similar to the studies on engine components in general, studies focusing specifically on fuel consumption also model the internal working of the engine. One such model was derived by Collins (1982) based upon his work at MITRE. He outlines the functional relationships between the classical aeronautical engineering equations and translates them into forms easily implemented for data analysis. Future research such as Schilling’s (1997) neural network model relies on Collins (1982) equations. An underlying engineering model driving the data analysis is a persistent theme in the research. Fuel consumption models often employ such baseline models which are grounded in aeronautics.

On the topic of estimating fuel consumption, Stolzer (2003) and Lockheed Martin (2014) both advocate examining the fuel burn during the cruise portion of the flight.

Garbi (2007) follows suit with a reference cruise model for a specific aircraft and analysis through a longitudinal motion model. Torenbeek (1997) presents an excellent treatment of the concept of cruise flight in relation to range (this concept is detailed in Chapter III). Woodbury and Srivastava (2012) performed linear discriminant analysis on FOQA data and verified that vertical speed corresponded to a higher fuel flow, whereas cruise flight tended toward values with a central mean and normal distribution. The reasoning for focusing upon cruise flight is simple: the cruise portion is usually the longest and most stable phase of any flight. The pitch, roll, and airspeed of the aircraft are intentionally close to constant. Since many other factors contributing to fuel consumption are nearly constant, the cruise portion represents the most stable flight region to observe engine fuel consumption. The concept of cruise flight data as a source for engine fuel consumption rounds out the research into the realm of FOQA analysis for fuel efficiency purposes. Chapter II closes with an examination of the techniques utilized to perform the research.

Filtering, Smoothing, and Estimation

A number of studies outlined in this chapter deal with advanced techniques (Artificial Neural Nets, Advanced Regression, Classification Trees, Cluster Analysis, etc). These techniques are aimed at anomaly detection within a fleet either for fuel consumption specifically, or one or several engine parameters in general. Although useful and effective, the goal of this study is neither classification nor anomaly detection (although anomalous fuel burn rates become evident in the analysis). The goal of this study is to quantify fuel burn rates for specific aircraft. In order to provide an estimate for fuel consumption, one should consider different algorithms. Simon (2008) offers a brief summary of algorithms proposed for engine health monitoring which includes weighted least squares, expert systems, Kalman filters, neural networks, fuzzy logic, and genetic algorithms. The key difference between the data presented in this thesis and those examined by Simon (2008) and others is the existence of positive autocorrelation within the data. Herein lays a key difference between smoothing and filtering techniques. Simon (2008) states smoothing has no benefit over filtering on datasets with constant bias. Unfortunately, the datasets utilized in this thesis are massively autocorrelated which drives the analysis toward smoothing techniques to provide estimates.

Staszewski et al. (2004) compose an entire text centered on concepts of signal processing for health monitoring. Their work harkens back to the earlier discussion on fleet health monitoring and diagnostic tools. Although centered more upon digital signals concerned with structural damage detection, the authors note the importance of considering noise reduction in a given dataset in a later chapter (pp. 165-173). They frame the concept of noise reduction in terms of classical smoothing techniques such as Fourier transforms, Wiener filters, and various other techniques. They also advocate the use of a simple moving average procedure computed using nearest neighbors. Additionally, they recognize that the classical techniques (Fourier transforms, etc.) can break down when the signal is non-stationary (time-dependent) (p. 171). They suggest the use of a windowed Fourier transform over a span of data that can be considered stationary. Based on the works of Staszewski et al. (2004), Simon (2008), and others, it is clear that the autocorrelated MFOQA fuel flow data provided for this study would require a smoothing technique capable of handling non-stationary, time-dependent data.

Cleveland (1979) introduced the concept of local regression on scatterplots, which he abbreviated LOESS. Much like the concept of windowed Fourier transforms described by Staszewski et al. (2004), the LOESS procedure uses weighted least squares over a localized span (sometimes called bandwidth) of data. The procedure is a nonparametric model which utilizes neighborhood weights about each point in the span (Martinez and Martinez, 2008, p. 520). The weights are derived from the bandwidth based upon a tricube function:

$$W(u) = \begin{cases} (1-u^3)^3; & 0 \le u \le 1 \\ 0; & \text{otherwise} \end{cases} \tag{1}$$

These weights are applied to either a first order weighted least squares fit or a second order polynomial fit. Higher order polynomials are possible, but rarely used (Cleveland, 1979). Cleveland's (1993) text defines the two parameters for LOESS: α = bandwidth (expressed as a percentage of the total number of data points), and λ = the order of the polynomial used in the Weighted Least Squares procedure (pp. 96-101). The choice of α and λ for the MFOQA fuel flow data is detailed in Chapter III. Furthermore, Cleveland (1994) advocates the use of the LOESS smoother on time series data (p. 154) noting the ability to fit trends while smoothing oscillations in time series data.

In summary, this chapter explored the body of work surrounding the use of FOQA data for aircraft fuel efficiency analysis. Chapter II also scoped the specific problem of quantifying an aircraft-specific fuel consumption figure. Beginning within the framework of fleet health monitoring and moving to the more specific topics of engine diagnostics and fuel consumption, the literature suggests different methods to harness FOQA data for fuel efficiency. On the specific topic of aircraft-specific fuel burn estimation, research points toward smoothing techniques as a viable methodology. With the relevant literature properly outlined, Chapter III moves on to the Methodology employed for the case study itself.

III: Methodology

Chapter I and Chapter II outlined the general philosophy behind utilizing MFOQA to realize gains in fuel efficiency and included an outline of the research in this arena. This Chapter outlines the specific methodology utilized toward an overall goal of extracting C-5M fuel burn estimates from noisy MFOQA data.

Case Study Data and Autocorrelation

Previous chapters discussed the large and unwieldy nature of FOQA data. AMC's MFOQA database is no exception. Analysts at AMC Headquarters at Scott Air Force Base provided the author with thirty test missions extracted from two aircraft (29 missions from one aircraft and one mission from a different aircraft). AMC contracted out the task of reducing and cleansing the raw MFOQA for the individual flights down to manageable file sizes. Serendipitously, the aircraft sensors which detect fuel flow readings record on one second intervals which matched the intervals on the cleansed files. The contracting team reduced down redundant and missing rows of data. The resulting datasets contain records of aircraft parameters and external environmental readings at one sample per second. Since the bulk of the provided data is from a single aircraft, the overall methodology approach is a case study on this single aircraft. As will be demonstrated, the methodology is applicable to the entire C-5M fleet.

Chapter II discussion noted cruise as most applicable flight regime for estimating fuel consumption. A simple model for capturing fuel burn during cruise flight associates the Gross Weight and Airspeed of the aircraft to the Fuel Flow rate. Details on this phenomenon will be discussed in later sections. To establish an initial framework, consider how Stolzer (2003) discovered both Airspeed and Gross Weight to be significant predictor variables on Fuel Flow rates for a FOQA-based study using ordinary least squares (OLS) regression techniques. It is worth noting that Stozler's (2003) dataset consisted of a single sample across several hundred FOQA datasets (missions), whereas this study utilizes many samples across only 30 FOQA datasets (missions). Thus, Stolzer's (2003) data is automatically independently distributed. The same assumption cannot be made for the data in this study. Nevertheless, running a simple linear regression still provides insights. The Stolzer (2003) study was rigorous and included several iterations of stepwise regression and resulted in uncorrelated predictors with excellent properties (low variance inflation factors, etc). From these results, it is reasonable to build an initial framework around a simple model which includes Stolzer's (2003) significant predictor variables.

OLS techniques are a natural starting point for data analysis. Using Gross Weight and Airspeed as regressors and Fuel Flow as the response, multiple linear regressions were performed in MATLAB software's "regstats" function on the associated columns of four specific MFOQA samples. The four samples represent "stable cruise" segments culled from the 30 test missions. They include the longest observed cruise (3.04 hours), the shortest observed cruise segment (0.84 hours), and two at-large samples near the mean cruise time of 1.5 hours. Details on the construction of these stable cruise segments are provided in the appendix. The resulting models exhibit low R-squared values, indications of lack of fit, and most importantly, significant values for the Durbin-Watson Statistic. These are all clear indications of autocorrelation. This is to be expected when examining MFOQA fuel flows over time. As the aircraft burns fuel, it becomes lighter thus reducing the overall Gross Weight. Since the fuel burn is a function of the Gross Weight of the aircraft, an overall trend exists but is masked by True Airspeed deviations. These Airspeed deviations are manifestations of throttle excursions occurring as the autopilot/autothrottle system corrects for Altitude deviations (Lockheed Martin, 2014). Such throttle excursions introduce autocorrelated noise into the system. The autocorrelated errors are evident through various statistical means. Bowerman, et al. (2005) provides the definition of the Durbin-Watson statistic on p. 291:

$$d = \frac{\sum_{t=2}^{n} (e_t - e_{t-1})^2}{\sum_{t=1}^{n} e_t^2} \qquad (2)$$

Table 1 below lists the values for the Durbin-Watson Statistic on the sample MFOQA datasets clearly indicating significant positive autocorrelation. It is worth noting that the p-values produced in Table 1 are normal approximations[1], but the result is clear. Notice the sample sizes are in seconds corresponding to the cruise times described in the previous paragraph.

Table 1 - Results of the Durbin Watson Test

Durbin-Watson Statistic Value	p-value	Sample Size
0.048662424	0	10955
0.051726953	0	3022
0.043579036	0	5051
0.044840468	0	5952

[1] See http://www.mathworks.com/help/stats/linearmodel.dwtest.html for details

The plots of the residuals of the four regressions shown in Figure 2 also exhibit the tell-tale signs of autocorrelation. They exhibit “sine wave” patterns as a clear violation of non-constant variance assumptions:

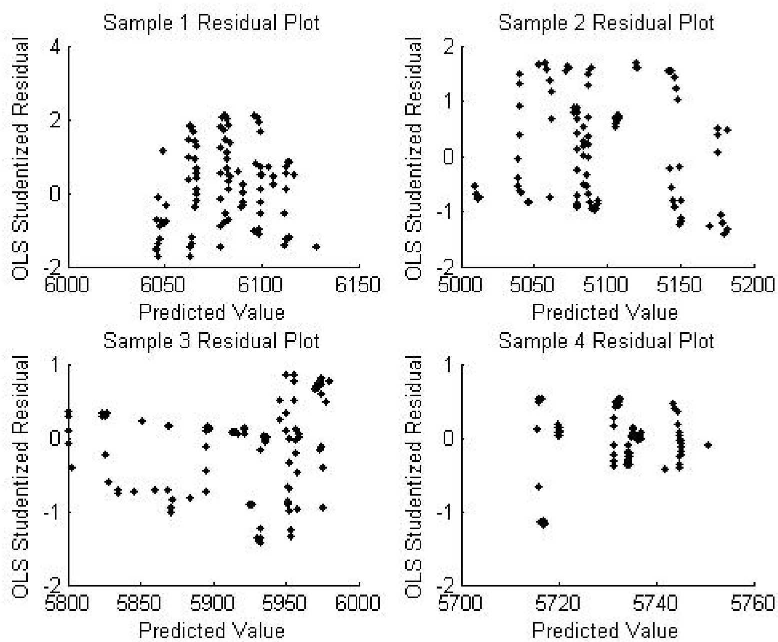


Figure 2 - OLS Residual Plots

Several of the studies discussed in Chapter II addressed the time series aspect of FOQA analysis. Li et al. (2011) and Woodbury and Srivastava (2012), in particular, speak to the time element as they attempt to model the entire flight envelope for anomaly detection. Their models are based upon cluster analysis and general linear models/Gaussian processes respectively. This study relies more upon smoothing techniques associated with time series analysis. Smoothing techniques are essential to this study in terms of understanding the actual fuel burn during cruise flight. Before examining the actual fuel burn and applicable smoothing techniques, a baseline fuel burn model must be established.

Specific Range and the Baseline Engineering Model

MFOQA provides a means of observing actual fuel consumption of C-5M engines. Analysis of these figures is meaningless without a baseline model for comparison. Luckily, the Technical Order specifications provide just such a baseline model (Lockheed Martin, 2012). The baseline engineering model in the Lockheed Technical Order is based upon the concept of Specific Range. Specific Range is an aeronautical equation used to describe fuel usage at cruise and is based upon the Breguet Range equation:

$$R = \frac{V(L/D)}{g * SFC} ln\left[1 + \frac{W_{fuel}}{W_{payload} + W_{structure} + W_{reserve}}\right] \tag{3}$$

Here g is the gravitational acceleration constant, V is the aircraft speed, and the ratio of weights describes the tradeoff between fuel and payload (Lee et al., 2004). The concept of Specific Range is employed in a number of ways to help quantify various fuel efficiency metrics (Reiman et al., 2011). Torenbeek (1997) includes an in-depth discussion of the derivation of the Specific Range curves and the basis for Equations (4), (5), and (6) involving airspeed and altitude. The Lockheed Martin (2014) study simplifies the Specific Range equations to estimable MFOQA parameters through the following derivations:

Consider the Specific Range quantity in terms of air nautical miles per pound of fuel burned:

$$SR = \frac{\text{Nautical Miles}}{\Delta W_{fuel}} \tag{4}$$

Dividing each term through by time, we have:

$$SR = \frac{\text{Nautical Miles/hr}}{\Delta W_{fuel} \text{ / hr}} \tag{5}$$

Which is re-written in terms of MFOQA observable terms as:

$$SR = \frac{V_{KTAS}}{FF} \tag{6}$$

where V_{KTAS} is the True Airspeed of the aircraft, and FF is the fuel flow reading in lbs/hr. Both are observable MFOQA parameters. Equation (6) offers a means to calculate a Specific Range value at a fixed Altitude and a given Gross Weight simply from observing the True Airspeed value (which is the Nautical Miles/hour value adjusted for altitude and temperature) (Lockheed Martin, 2014). Since the True Airspeed is a function of altitude and temperature, the C-5M Technical Order presents flight-tested charts providing plots of Specific Range values at a fixed altitude for a given Gross Weight and Mach Number (True Airspeed in terms of percentage of the speed of sound) (Lockheed Martin, 2011). Figure 3 is an example of a Specific Range chart similar to the one in the Technical Order. Families of curves are printed for a fixed Altitude with respect to Gross Weight values at 10,000 pound intervals. The curves plot Specific Range versus Airspeed in Mach. Figure 3 displays the curves for five Gross Weights valued from 700,000 lbs to 740,000 lbs. Notice the non-linear relationship between Airspeed and Specific Range which indicates an “optimal” airspeed is quantifiable for every combination of Gross Weight and Altitude.

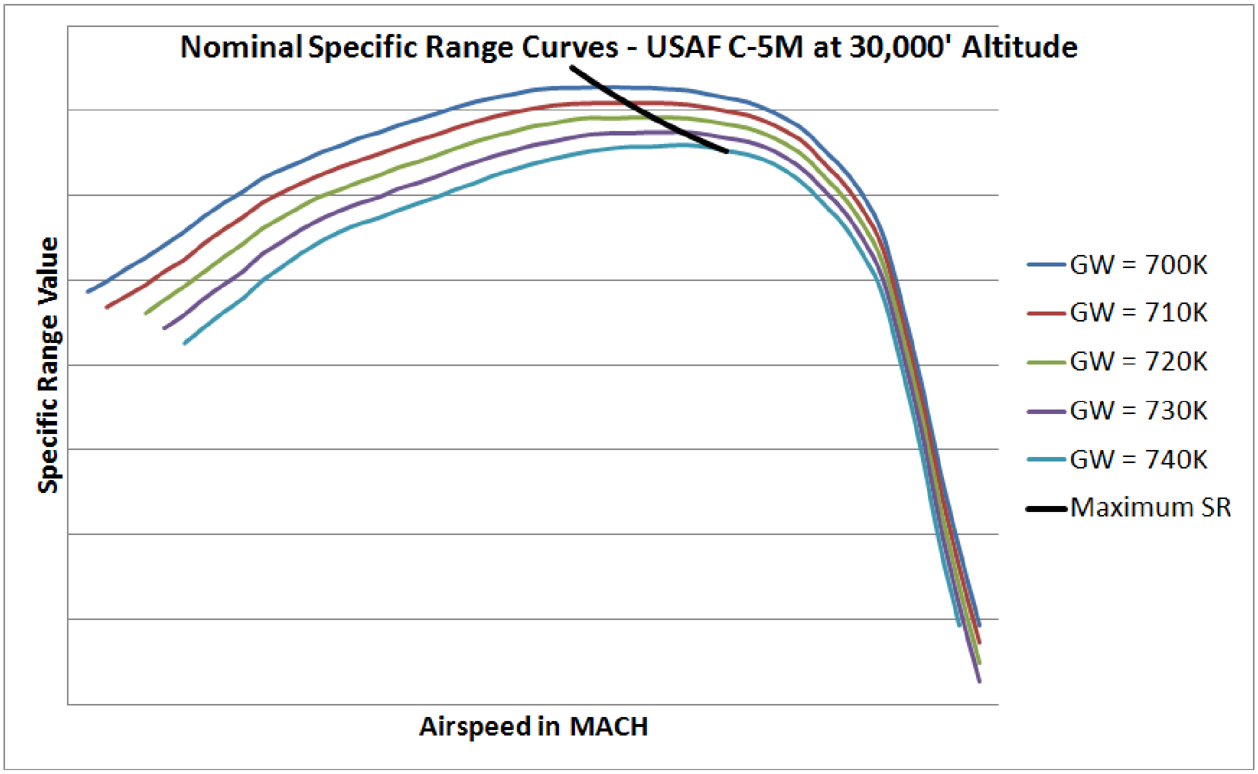


Figure 3 - Nominal Specific Range Curves

Finally, notice that Equation (6) can be re-written in terms of Fuel Flow:

$$FF = \frac{V_{KTAS}}{SR} \tag{7}$$

Thus, for a given set of MFOQA observations (Altitude, Gross Weight, True Airspeed), it is possible to obtain a Technical Order “baseline” Fuel Flow measure. This quantity can then be compared to the actual MFOQA Fuel Flow observation at a specific point in time. Integration over time of the observed cruise portion provides a total fuel burn estimate for both the baseline (derived from Specific Range values based on MFOQA Altitude, Gross Weight, and Airspeed) and the observed (the actual MFOQA Fuel Flow reading).

The MIF Project and Interpolating Specific Range Values

The Technical Order charts such as the example in Figure 3 are useful for understanding the concept of Specific Range visually, but are not ideal for obtaining precise Specific Range values. Simply plotting the inputs (Airspeed and Gross Weight) requires a keen eye and provides only rough estimates at best. Also, the precise MFOQA readings naturally require interpolation between the curves since the Gross Weight values are only plotted at 10,000 lb increments. Luckily, through the efforts of an ongoing fuel efficiency project titled "Mission Index Flying" (MIF), the charts themselves were converted over to tabulated values. MIF is based upon industry best practices of quantifying the optimal airspeeds (i.e., flying airspeeds corresponding to the maximum on the Specific Range curve) discussed earlier and plotted on Figure 3 (Mirtich, 2011). A MIF database of approximately 26,000 records which contains tabulated values for a Specific Range for a given Altitude, Mach speed, and Gross Weight was obtained. The tabulated values are easily interpolated to provide precise Specific Range estimates. Table 2 below outlines the ranges on the MIF database:

Table 2 - MIF Database Description

Input	MIF Database Ranges	MIF Database Increments
Altitude	27,000'-45,000'	1000'
Mach Airspeed	0.39-0.825	0.005
Gross Weight	400,000 lbs - 840,000 lbs	10,000 lbs

Using Equation (7) above, the baseline Specific Range values are easily converted into instantaneous Fuel Flows for comparison with the actual Fuel Flow observations. An interpolating function can be used or the values can be rounded to the nearest entry among the 26,000 available combinations. For this study, an interpolation scheme was implemented using MATLAB's "scatteredInterpolant" function.

Establishing Stable Cruise Criteria and Parsing Data

The 30 test samples provided by AMC yielded 45 MFOQA cruise portions which fall into the ranges in Table 2. Visual Basic (VBA) code was written to quickly parse an entire mission (one of the thirty samples) into usable cruise segments within the Altitude ranges of Table 2. The logic for focusing upon stable cruise flight segments was outlined in Chapter II. The VBA code limits "stable cruise" to the following criteria: 1) At least one hour of cruise (3600 records), 2) Of the one hour cruise, the first and last five minutes are discarded to allow for level-off from climbs and preclude capturing initial climb to the next altitude, 3) A steady altimeter reading (±25') to reduce noise. Pseudo-code is provided in Appendix A. Precise Specific Range values for each record in a stable cruise sample arise from plugging in observed MFOQA Altitudes, Gross Weights, and Mach speeds. The stable cruise segments also record the observed Fuel Flow during flight. These data are used to calculate the actual fuel burn estimate for comparison to the baseline.

Actual Fuel Burn Estimate and LOESS Smoothing

This section returns to the concept of quantifying the specific fuel burn for a specific engine (which aggregates into an estimate for the fuel burn of the aircraft as a whole). With the autocorrelation detailed, stable cruise samples parsed, and a baseline fuel burn calculated, the actual fuel burn estimate can be established and compared to the baseline. The result is a good estimation of the true fuel burn “degrade” of the engine. Implementation of the LOESS smoother upon noisy MFOQA fuel flow data is the method employed in this study.

The section on autocorrelation and the introduction of the smoothing technique known as LOESS set the stage for the methodology involved in calculating the actual fuel burn estimate. There are many techniques available to deal with autocorrelation. These include the Cochrane-Orcutt Method, ARMA, ARIMA, (Montgomery et al., 2012, p. 482), the Batch Means method (Law, 2007, pp. 520-522), and others. Each technique has advantages and drawbacks.

The LOESS smoother described in Chapter II has some distinct advantages as outlined by Cleveland and Loader (1996). First, although the method itself is nonparametric, it is easy to understand and interpret. It is also an adaptable and flexible method that can deal with different distributional assumptions. The use of a local model and the choice of bandwidth and polynomial order selection also contribute to the flexibility of the method. According to Cleveland and Loader (1996), none of these aspects alone make the LOESS smoother a preferred choice over splines or other kernel methods. Taken as whole, however, the adaptability and flexibility of the LOESS model make it an excellent choice for time series data (such as MFOQA fuel flows) which Cleveland (1993) describes as “functions that defy description by simple parametric functions” (p. 154).

The LOESS smoother does have a few drawbacks. First, the nonparametric nature of the procedure precludes specification of a rigid structural relationship between the independent and dependent variables as is done with normal regression techniques. Since the goal of this study is estimation rather than a structural model, the nonparametric nature of the procedure is not overly concerning. Second, the LOESS procedure itself is admittedly computationally intensive. LOESS performs a weighted least squares regression for each point in the span. In the past, this may have been a factor for large datasets, but modern computing power makes LOESS implementable on large datasets. Diagnostics such as "goodness of fit" for LOESS are difficult to quantify and interpret but some insight can be garnered from residual analysis (Jacoby, 2000). Finally, the task of designating the LOESS parameters (and thus fine-tuning the amount of smoothing) is not trivial. Even small changes to the parameters can drastically affect the estimates. Despite these drawbacks, LOESS is still an excellent choice for the MFOQA fuel flow estimation since it is specifically designed to deal with noisy data.

LOESS Smoothing Parameters for C-5M MFOQA Fuel Flow

Utilizing LOESS to produce the MFOQA fuel flow estimates is achievable, but requires careful attention to the specification of the LOESS parameters. The choice of α and λ are important. Cleveland and Loader (1996) describe the choice of α as a tradeoff between variance reduction and bias. Higher values of α result in larger spans and a smoother curve. For the MFOQA analysis, the goal is noise reduction and the preservation of the underlying trend in the fuel flow response. Recall that the fuel flow responses decrease over time due to reduction in the Gross Weight of the aircraft. This phenomenon is “masked” by noisy autothrottle and Airspeed inputs which, in turn, distort estimates of actual fuel burn. To counter this effect, LOESS is employed to smooth out the noise and provide a clearer estimate of actual fuel burn for comparison. In a similar manner, LOESS smoothing on the True Airspeed value used in the baseline estimate reduces noise resulting in a smooth baseline curve.

Cleveland (1993) describes LOESS parameter selection as an iterative procedure and encourages “educated first guesses” (p. 96). For the smoothing parameter α, Cleveland offers a range of values from 0.25 to 1 as a heuristic. With regards to the 45 stable cruise segments, 75% are below two hours in duration (recall that the stable cruise criterion for duration was at least one hour) with the mean of all 45 near 1.5 hours. This means that $\alpha = 0.25$ equates to approximately 25 minutes on average. For the aircraft weights observed in the 45 stable cruise segments, a quick approximation for fuel burn is roughly 20,000 lbs/hour (Lockheed Martin, 2012) meaning that the model is seeking to detect changes in fuel flow responses over a change in Gross Weight averaging approximately 5,000 lbs. Both Cleveland and Loader (1996) and Simonoff (1996) view boundary regions as a major consideration in the choice of α. Indeed, the nearest neighbors tricube weighting employed in LOESS treats points on the tails of the bandwidth differently than an interior point. In terms of MFOQA, it is reasonable that a change of 5,000 lbs would register a measurable change in fuel flow responses. Simonoff (1996) offers techniques based upon Kernel densities which may yield more “optimal” values of α. He further explores the effects of autocorrelation on smoothing, noting that the existence of autocorrelation suggests the use of a higher value for α. Efforts to finetune the smoothing parameter have merit, but for the reasons outlined above, $\alpha = 0.25$ is a reasonable choice for this study.

The choice of λ (the degree of the polynomial used in the local regression) should attempt to model the underlying trend. Cleveland (1996) notes that "gentle curvature" with no local maxima or minima would allow for a local linear fit (p. 98). Jacoby (2000) notes a linear fit is appropriate if a general monotonic pattern is discernible from the raw data. For the MFOQA data, an argument can be made for both the linear and quadratic models ($\lambda = 1$ and $\lambda = 2$ respectively). The very fact that fuel burn can be estimated at roughly 20,000 lbs/hour seems to confirm a linear trend and plots of the raw data (seen in Figure 9) seem generally monotonic (although noisy). It is worth considering, however, engineering models (such as Figure 3) which demonstrate decidedly nonlinear relationships over vast spans of aircraft weights. Since LOESS smoothing with both linear and quadratic models is easily implemented in MATLAB, a simple solution is to run each method on a limited dataset and examine preliminary results to further justify the proper choice of λ.

LOESS Residual Diagnostics

At the beginning of the chapter, four stable cruise segments were utilized to demonstrate the autocorrelation present in the MFOQA fuel flow responses. Recall that these data were the shortest duration, longest duration, and two at-large segments near the mean of 1.5 hours. It is now clear that these segments were pulled from the larger set of 45 stable cruise samples. Along with demonstrating autocorrelation, these four segments are ideal for examining LOESS diagnostics.

Jacoby (2000) describes how a properly specified LOESS curve would account for any systematic dependencies in bivariate data, thus the residuals from the model should contain no discernible pattern. Indeed, Cleveland (1993) espouses the use of residual analysis as a primary diagnostic for LOESS (pp. 103-104). Jacoby's (2000) definition of a LOESS residual:

$$e_i = y_i - \hat{g}(x_i) \tag{8}$$

follows the familiar definition used in ordinary regression. With residual diagnostics, LOESS bridges a compromise between nonparametric and parametric modeling. In particular, the use of residual dependency plots to check for non-constant variance, alongside Normal q-q plots to check for normality (Cleveland, 1993, pp. 103-109) are familiar diagnostics used to test the classic regression assumptions (Montgomery et al., 2012, pp. 129-130). Since it is impractical to examine 45 sets of residual plots, returning to the four segments used to describe the autocorrelation is adequate for LOESS residual analysis. Residual analysis on this subset helps justify parameters choices and verify the methodology prior to analyzing the full dataset.

Cleveland (1993, p. 103) and Jacoby (2000) both advocate the use of "residual dependence plots" as LOESS diagnostics. The idea is to plot the residuals from the LOESS fit against the independent variable. The logic is similar to classical regression in the sense that the LOESS smoother should capture the underlying trend between the independent and dependent variable leaving nothing but white noise in the residuals. With large datasets, it is appropriate to run the LOESS smoothing algorithm on the residuals themselves with the expectation that the new smoothed curve is a line about a mean of zero (Jacoby, 2000).

Figure 4 and Figure 5 show the residual dependence plots for the four sample cruise segments for both the linear and quadratic LOESS procedures:

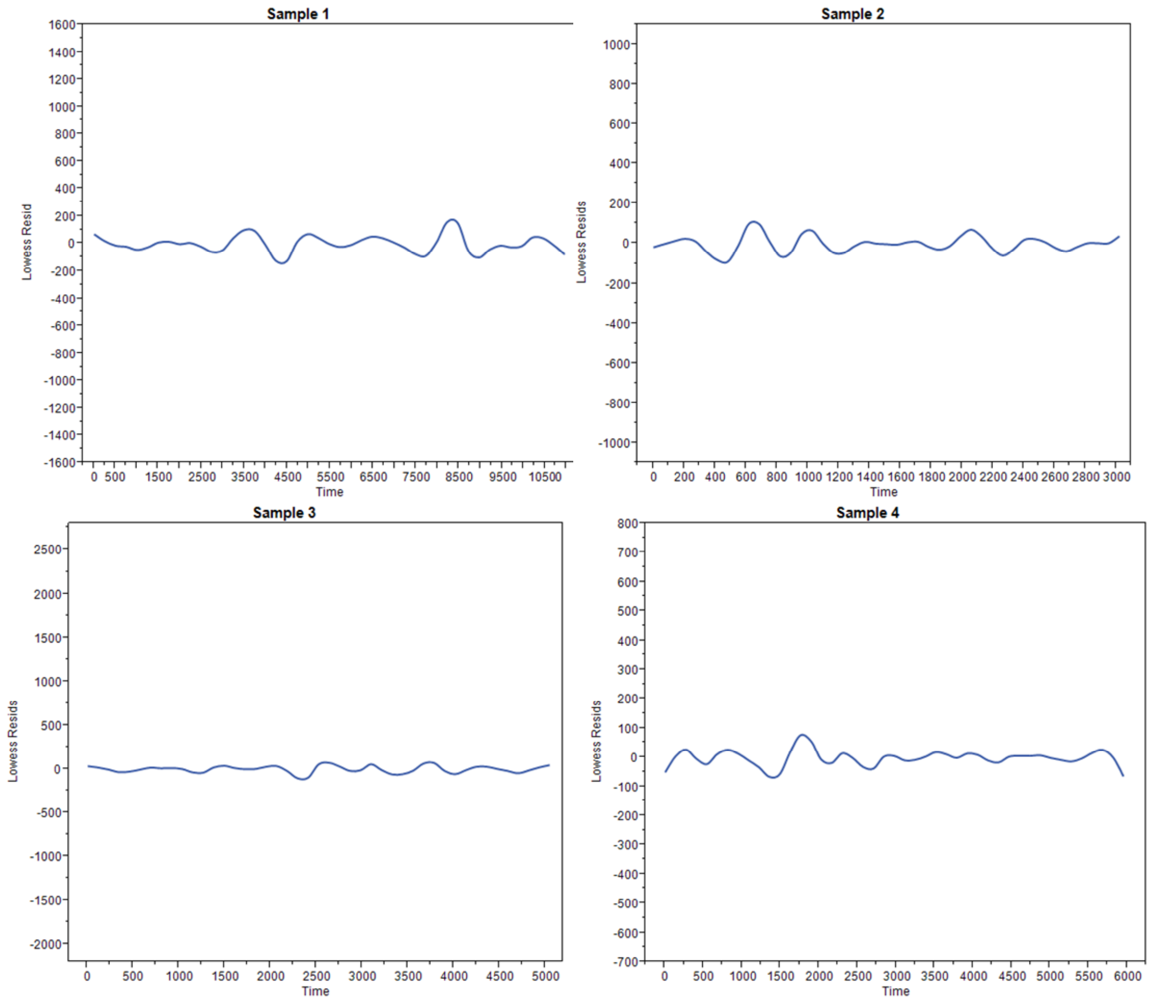


Figure 4 - Residual Dependency Plots for the Linear Fit

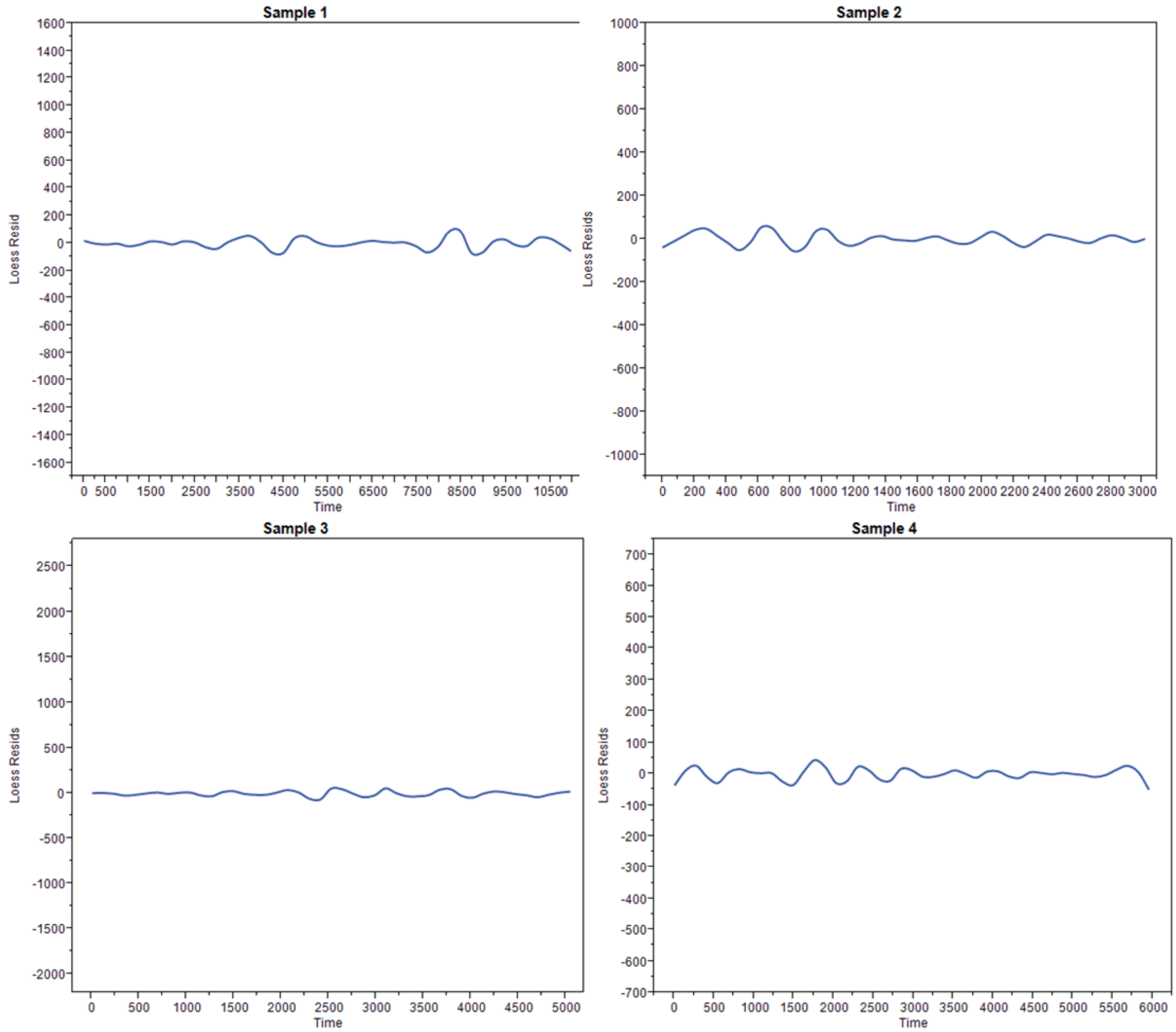


Figure 5 - Residual Dependency Plots for the Quadratic Fit

Both sets of plots result in smoothed lines near zero, but with some oscillations. These oscillations indicate that the autocorrelation is still present. This is not quite as concerning for the nonparametric nature of LOESS, but it is worth noting that the quadratic model deals with the autocorrelation slightly better. The overall trend toward a mean of zero is encouraging. These plots also hint that the quadratic fit ($\lambda = 2$) may be preferred for this dataset.

A second LOESS diagnostic is the familiar Normal q-q plot (Cleveland, 1993, pp. 108-109) which provides justification for the weighted least squares fit utilized within LOESS.

Figure 6 and Figure 7 below display the Normal q-q plots for the linear and quadratic fits. They are nearly identical. The accompanying box plots show some outliers, but the sample sizes are large enough that the data is not unduly influenced. For smaller datasets with potential outliers, a robust version of LOESS is available (Cleveland, 1993, pp. 110-116). The robust LOESS procedure involves iterative re-weighting of the least squares fit based on the Median Absolute Deviation of the residuals. The robust version is not considered for this study.

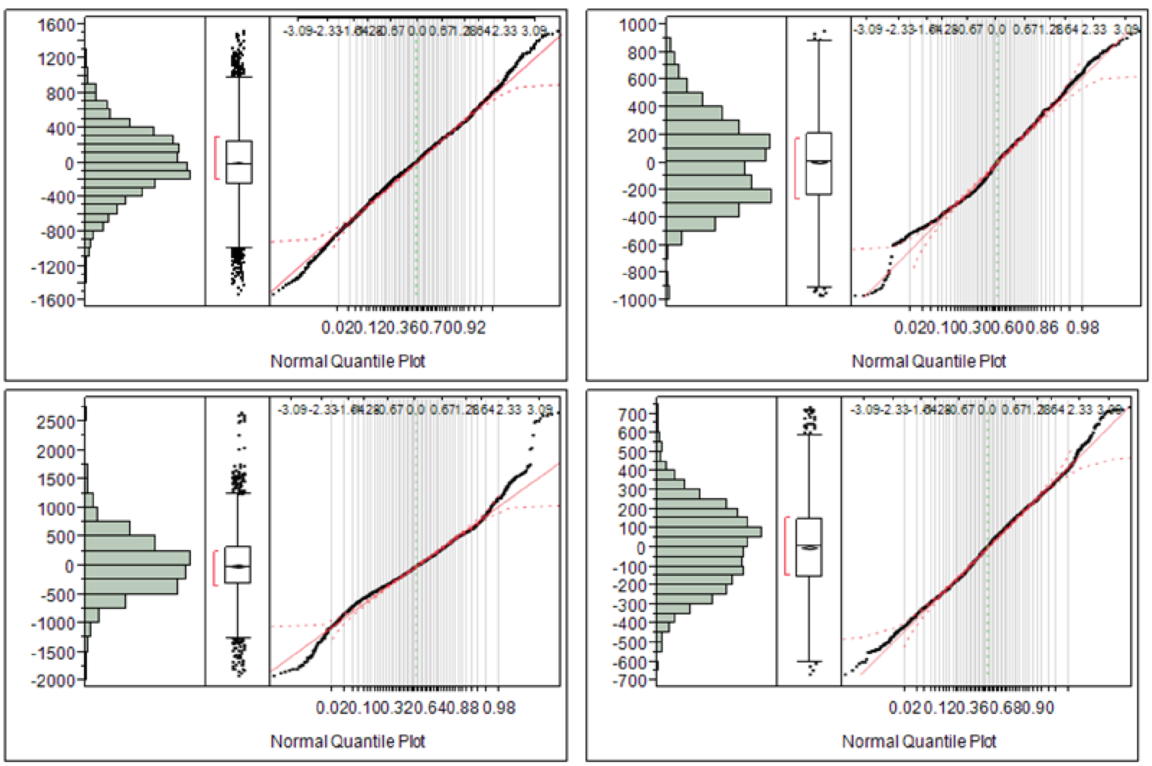


Figure 6 - Normal Quantile Plots for the Linear Fit

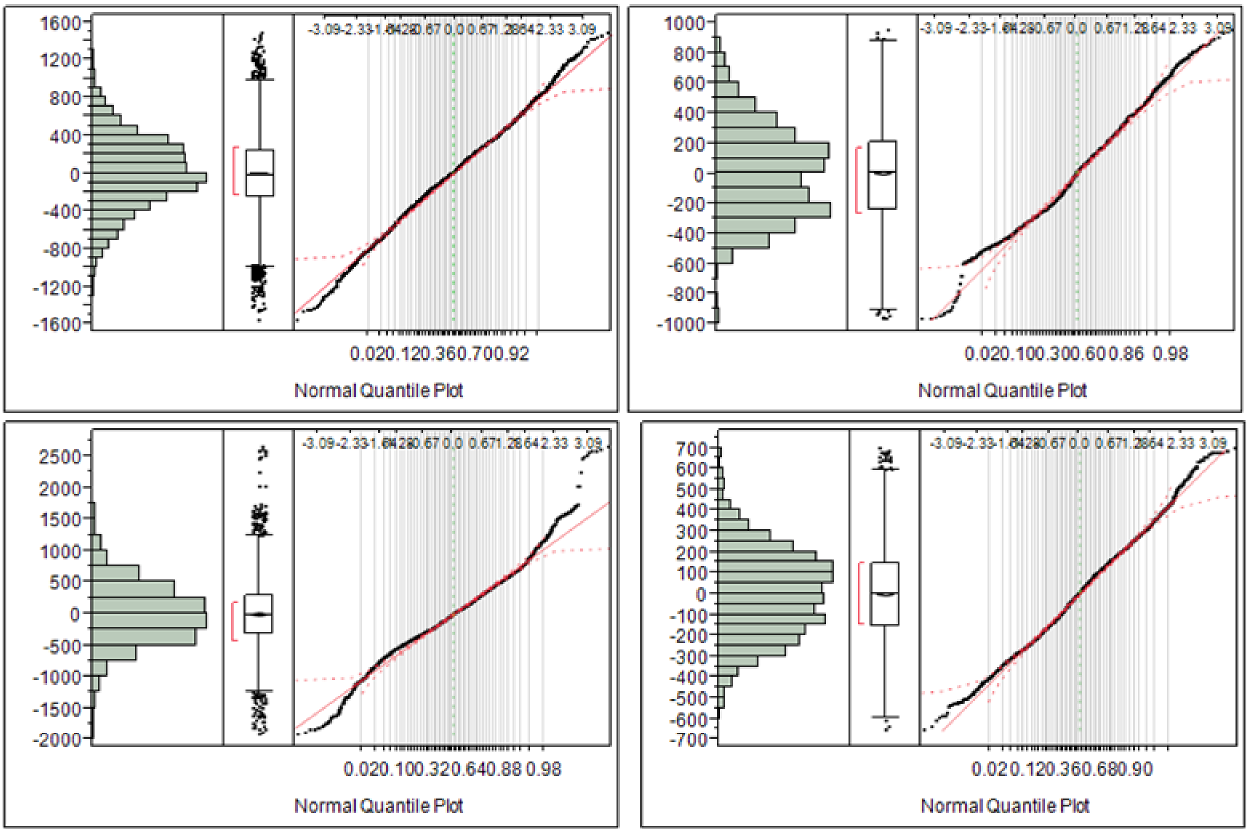


Figure 7 - Normal Quantile Plots for the Quadratic Fit

Before moving on to the results of the full analysis presented in Chapter IV, it is worth noting that further LOESS diagnostics exist. These involve techniques aimed at quantifying corollaries to some classic statistical techniques such as ANOVA tables, F-values, R^2 values and the like. This is accomplished through a variety of cross-validation, bootstrapping techniques, and theory from Kernel densities. For LOESS, classical statistical inference becomes somewhat dubious and difficult to interpret. In the strictest sense, the LOESS smoother does not partition the sum of squares for error in a way that allows for the classical ANOVA assumptions to hold (Jacoby, 2000). The interested reader should refer to Jacoby (2000) and Simonoff (1996) for a discussion on these diagnostics. Certain problems may gain insight from these calculations, but little value is added for this study. The outcomes of the residual analysis presented above are sufficient to move forward.

Comparison and Summary

Figure 8 below summarizes the methodology presented in this Chapter. The methodology itself is applicable to any FOQA dataset, and is tailored to the C-5M for this study.

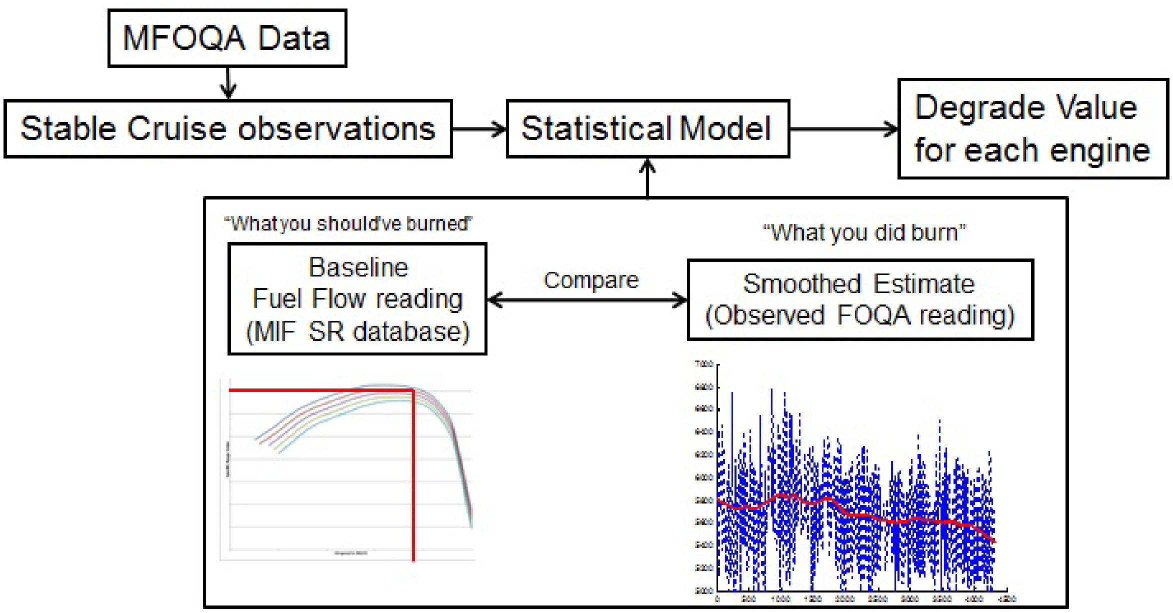


Figure 8 - Methodology Summary

Raw MFOQA is parsed into stable cruise portions based upon the criteria outlined above. The goal is to key in on flight segments where the aircraft and the engines are at their most stable. Once parsed, three MFOQA inputs (Gross Weight, Altitude, and Mach Airspeed) are used to compute the baseline fuel flow. This baseline number is an interpolation using Specific Range culled from the MIF database. In simple terms, this baseline represents "what the aircraft should've burned". LOESS smoothing on the True

Airspeed input reduces the noise in the baseline response. Next, the recorded fuel flows are smoothed using the LOESS procedure to produce an estimate of actual fuel burn. The final step is to integrate both of these curves and record the difference. This difference divided by the baseline estimate is the degrade value. For this study, all of the calculations are performed in MATLAB and are outlined in the pseudo-code in Appendix A. A graphical example of the model output is presented in Figure 9 below:

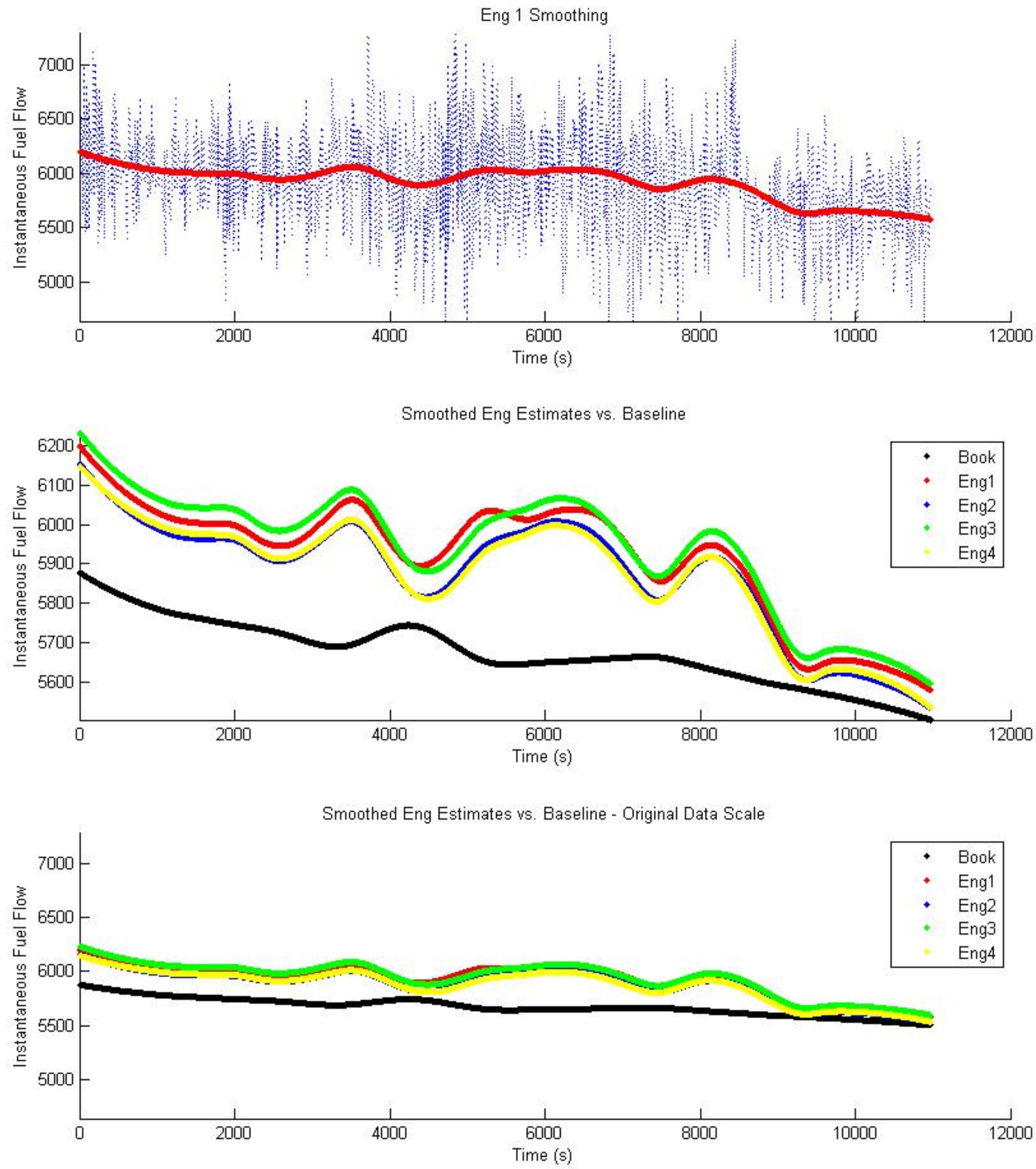


Figure 9 - Smoothing Example

In this example, the top plot shows LOESS smoothing against the raw MFOQA fuel flow responses for a single engine. The middle plot shows the four smoothed MFOQA responses (one for each engine) against the smoothed baseline fuel burn. The bottom plot is the same as the middle plot but shown on the same y scale as the top plot. This demonstrates how the LOESS smoother reduces the noise in the data. The smoothing technique is LOESS with $\alpha = 0.25$ and $\lambda = 2$ for the reasons discussed above. The area between each smooth curve and the baseline curve represents the difference in fuel burn in pounds. Expressing this difference as a percentage of the baseline produces the degrade number. This degrade number is the overall goal of the study and is applicable for mission planning as discussed in Chapter I. Results of the implementation of this methodology on the full dataset are presented in Chapter IV.

IV. Analysis and Results

The first three chapters laid the groundwork for the fuel burn analysis specific to the C-5M. This analysis is of interest to AMC for the reasons outlined in Chapter I and is the focus of this chapter.

Quantifying the fuel degrade value

The methodology outlined Chapter III and summarized in Figure 8 was applied to 45 stable cruise observations. The model output is in the form of four degrade values (one value for each engine). These numbers are then averaged providing the "tail-specific" fuel degrade for the entire aircraft. This final number is an estimate of the fuel burn performance for the aircraft. The tail-specific degrade value can then be applied to flight planning which results in more accurate fueling procedures.

For this study, 45 stable cruise segments were obtained. Of the 45 stable cruise segments, 40 observations come from a single aircraft. The remaining 5 observations are from a different C-5M and work to validate the procedure. Two tables below were constructed from the results of the 45 cruise segments. The first table provides summary statistics for the 40 observations from the case-study aircraft (Aircraft #1) and the second table summarizes the 5 observations from Aircraft #2. The tables were constructed using Excel's Data Analysis Add-In which provides concise summary statistics.

Table 3 - Summary statistics for Aircraft #1 (n=40) samples

Engine #1 Degrade		*Engine #2 Degrade*		*Engine #3 Degrade*		*Engine #4 Degrade*	
Mean	0.0466	Mean	0.0369	Mean	0.0482	Mean	0.0366
Standard Error	0.0016	Standard Error	0.0017	Standard Error	0.0020	Standard Error	0.0015
Median	0.0455	Median	0.0350	Median	0.0467	Median	0.0352
Standard Deviation	0.0101	Standard Deviation	0.0106	Standard Deviation	0.0128	Standard Deviation	0.0096
Sample Variance	0.0001	Sample Variance	0.0001	Sample Variance	0.0002	Sample Variance	0.0001
Range	0.0436	Range	0.0453	Range	0.0587	Range	0.0404
Minimum	0.0293	Minimum	0.0203	Minimum	0.0245	Minimum	0.0218
Maximum	0.0729	Maximum	0.0656	Maximum	0.0832	Maximum	0.0622
Sum	1.8635	Sum	1.4753	Sum	1.9274	Sum	1.4651
Count	40.0000	Count	40.0000	Count	40.0000	Count	40.0000
Confidence(95.0%)	0.0032	Confidence(95.0%)	0.0034	Confidence(95.0%)	0.0041	Confidence(95.0%)	0.0031
Confidence Interval Bounds							
Lower	0.0434	Lower	0.0335	Lower	0.0441	Lower	0.0336
Upper	0.0498	Upper	0.0403	Upper	0.0523	Upper	0.0397

It is useful to examine the fuel degrade results for each individual engine. Recall that the degrade percentages shown are the end product of the methodology presented in Chapter III. These figures are a ratio of the observed excess fuel burn (obtained from the smoothed MFOQA Fuel Flow reading) to the smoothed baseline fuel burn. Referring back to Table 3, it is noticeable that engine #1 and engine #3 exhibit a higher burn rate than engines #2 or #4. This comes to bear in the output. The summary statistics include the half-width of the classic t confidence interval as described by Bowerman, et al. (2005) on p. 57:

$$\bar{y} \pm t_{\alpha/2,n-1}\left(\frac{s}{\sqrt{n}}\right) \qquad (9)$$

For this data, Excel uses a 95% Confidence level and we have $n = 40$. Of note, the intervals for engines #1 and #3 are $[0.046 \pm 0.00322]$ and $[0.048 \pm 0.00409]$ respectively. This is a critical finding since the bounds on these intervals are above 4% providing statistical evidence that these engines are burning above the advertised 4% degrade. The intervals for engines #2 and #4 are $[0.0369 \pm 0.00335]$ and $[0.0366 \pm 0.00307]$ respectively. Engine #2's bounds contain the advertised 4% value whereas Engine #4's upper bound is very slightly below 4%. The overall tail-specific degrade is the average of the 4 engine means is 0.04207. The figure is slightly above 4%, which indicates the case study aircraft is burning slightly more fuel than is accounted for in the 4% flight planning figure. Critically, this provides evidence that the ramp fuel loads on this particular aircraft are slightly too low and run the risk of causing costly diverts.

Similar analysis on Aircraft #2 data in Table 4 provides confidence intervals for all four engines on a limited sample size for $n = 5$.

Table 4 - Summary statistics for Aircraft #2 (n=5) samples

Engine #1 Degrade		*Engine #2 Degrade*		*Engine #3 Degrade*		*Engine #4 Degrade*	
Mean	0.0332	Mean	0.0292	Mean	0.0407	Mean	0.0329
Standard Error	0.0030	Standard Error	0.0031	Standard Error	0.0031	Standard Error	0.0032
Median	0.0337	Median	0.0298	Median	0.0405	Median	0.0328
Standard Deviation	0.0066	Standard Deviation	0.0068	Standard Deviation	0.0070	Standard Deviation	0.0072
Sample Variance	0.0000	Sample Variance	0.0000	Sample Variance	0.0000	Sample Variance	0.0001
Range	0.0165	Range	0.0168	Range	0.0183	Range	0.0166
Minimum	0.0240	Minimum	0.0197	Minimum	0.0311	Minimum	0.0234
Maximum	0.0405	Maximum	0.0364	Maximum	0.0494	Maximum	0.0399
Sum	0.1660	Sum	0.1460	Sum	0.2035	Sum	0.1645
Count	5.0000	Count	5.0000	Count	5.0000	Count	5.0000
Confidence(95.0%)	0.0082	Confidence(95.0%)	0.0085	Confidence(95.0%)	0.0087	Confidence(95.0%)	0.0089
Confidence Interval Bounds							
Lower	0.0250	Lower	0.0207	Lower	0.0320	Lower	0.0240
Upper	0.0414	Upper	0.0377	Upper	0.0494	Upper	0.0418

Notably, three out of four individual means are slightly below 4%; however, the limited sample size precludes much further insight. Each of the individual engine confidence bounds contains 4% with the exception of Engine #2. Additional data would reveal whether or not this particular aircraft is burning fuel at a different rate than the case study aircraft. A confidence interval below 4% would hint at the idea the aircraft is being loaded with too much fuel and that savings could be obtained by adjusting the degrade value. The fact that the results of the case study and second C-5M data are similar is some evidence verifying the overall analysis.

Computer Flight Plan Validation

Providing face validity is important to any data-based study. For AMC leadership to consider MFOQA data analysis for fuel efficiency, a validation framework should be established. A straightforward approach to validate the model presented in this study is through comparison with AMC's own flight planning output. AMC utilizes proprietary Computer Flight Planning Software (CFPS) to build aircrew Computerized Flight Plans (CFP). The author obtained CFPs matching 12 of the 45 stable cruise segments. Matching Gross Weight MFOQA readings to CFP estimates, the author analyzed matching sub-segments of the 12 cruise segments to the corresponding CFP waypoints. The pseudo-code for this procedure is included in the Appendix. The resulting analysis compares the CFP planned fuel burn, the MFOQA-observed fuel burn, and the baseline model fuel burn for each sub-segment.

Table 5 - CFP validation data

		"Planned Burn" with CFP inputs	"Actual Burn" FOQA Model	"Should've Burn" FOQA Inputs
Altitude	Takeoff Gross Weight	CFP Fuel Burn (FLRM Differential)	FOQA Fuel Burn (Model)	Baseline Fuel Burn (Book Answer)
310	764K	25,800	25,495	24,358
310	764K	17,500	18,173	17,547
360	643K	16,200	16,545	15,791
360	647K	13,200	13,088	12,269
310	841K	14,800	15,052	14,351
330	841K	52,500	52,099	50,385
350	841K	22,200	21,639	20,282
350	711K	17,700	17,818	17,062
320	730K	17,500	17,245	16,543
330	721K	23,700	23,454	22,266
350	721K	19,100	18,595	18,078
330	749K	16,100	16,477	15,868

Table 5 exhibits a variety of matching cruise segments observed at various Altitudes and Gross Weights. The duration of the stable cruise segments was calculated from both the MFOQA-observed data and the corresponding CFP waypoints. In certain cases, the planned duration (from the CFP) differs slightly from the MFOQA observed duration, but in no case is the difference drastic enough to cast doubt upon the match. From equation (3) and equation (7) described in Chapter III, the “baseline” fuel burns obtained from the electronic database will change based on Altitude and Gross Weight and the interpolated values are listed in the “Baseline Fuel Burn” column.

The differences in the columns in Table 5 yield the individual degrade values for each of the 12 matching stable cruise segments. These values are the difference between the data and the baseline expressed as a percentage of the baseline (the same as the output from the overall model described in Chapter III). The means of these differences provides an estimate of the overall degrade using CFP calculations and the model output. The 95% confidence intervals about these means are $[4.64 \pm 1.72]$ for the planned values and $[4.61 \pm 0.76]$ for the model output. It is remarkable that each of these values encompasses the advertised 4% degrade, but that the planned values exhibit quite a bit more variability than the model. The overall result provides validity to the implementation of the methodology described in Chapter III since this methodology is completely independent of the computations involved with AMC’s CFP program. A larger sample of matching cruise segments could provide further insight into how well the model performs as compared to AMC’s flight planning software.

V. Conclusions and Recommendations

Using MFOQA to Quantify Fuel Degrade

The results presented in Chapter IV demonstrate the usefulness of MFOQA in terms of quantifying a fuel degrade figure for an individual C-5M. Harnessing MFOQA required quite a bit of data cleansing, but not to the point that implementation on a wide scale is prohibitive. There are a few reasons for this. First off, there is only a very small subset of the MFOQA database needed for fuel consumption analysis. The methodology employed in this study really only pulls four quantities from the larger dataset: 1) Fuel Flow (1 reading per engine), 2) Gross Weight, 3) Altitude, and 4) True Airspeed (interchangeable with Mach speed). This relatively small subset of MFOQA was pulled for this study using contracted algorithms and VBA code. The process can easily be replicated.

The methodology summarized in Figure 8 is intended to provide a good estimate of the actual performance of the engine in terms of fuel consumption. It utilizes various techniques to reduce noisy autothrottle excursions while attempting to preserve the underlying trend in fuel flow responses. As outlined in Chapter II and Chapter III, there are many other mathematical and statistical techniques which could apply to quantifying MFOQA fuel flow. The technique used to determine the fuel degrade value should be validated. The precision and quantity of MFOQA data makes it a very reliable source for any number of techniques.

The case study outlined in Chapter III and demonstrated in Chapter IV provides a framework for determining a tail-specific fuel degrade quantity for an individual C-5M.

For the reasons discussed in Chapter I, a precise fuel degrade figure can lead to improved mission planning and better overall fuel efficiency for an individual C-5M. The individual fuel degrade figure coupled with aircraft-specific fuel planning can lead to better overall fleet fuel efficiency.

Fleet Fuel Efficiency and Maintenance/Operations Implications

AMC is operating the C-5M under the assumption that the engines are operating at a 4% degrade value. The 4% value accounts for deterioration and other differences between the operating conditions and the flight test data provided in the original technical order. This value translates into a "pad" factor added to the ramp fuel calculated to perform a mission. Chapter IV results show the case study aircraft degrade at an average of 4.2% meaning the case study aircraft is likely being under-fueled. As discussed in Chapter I, razor thin fuel loading procedures could lead to costly diverts if a degrade factor is undercut. Conversely, Aircraft #2 samples are trending toward a number less than 4% meaning that this aircraft could be loading excess fuel and incurring unnecessary cost. Chapter I discusses how over-fueling the aircraft wastes fuel and incurs added cost. Whatever the case, there is evidence that a blanket value of 4% for the entire C-5M fleet is most likely incorrect and wasting money and resources. Examining each C-5M individually would lead to refined values for each aircraft and a possible overall increase in fleet-wide fuel efficiency.

Although quantifying the fuel degrade number is useful for fuel planning, the drastic differences in the performance of the individual engines provide evidence that the engines themselves are consuming fuel at different rates. The overall goal of this study is not anomaly detection per se, and analysis of MFOQA alone cannot account for the variation in fuel burn. This analysis simply presents the results as they are, namely, that a difference exists. In other words, this MFOQA fuel study cannot state “why” a certain engine exhibits anomalous fuel consumption, but simply that it is occurring. Many of the studies outlined in Chapter II harness FOQA for anomaly detection in a similar manner. Within the context of AMC operations, identifying anomalous fuel consumption in an engine is still very useful even if there is no upfront solution to the problem. Simply identifying the problem is useful. Utilizing MFOQA provides maintenance personnel a method of identifying “bad actors” within the fleet independent of the normal maintenance and inspection procedures. Of course this also highlights the associated challenges of implementing such analysis fleet-wide. For example, if an aircraft is sent off to Depot maintenance and the engines are fine-tuned (or even swapped) then the entire analysis must be re-run. Logically, the degrade number before and after a major maintenance action would tend to differ.

Finally, aircraft operations should include consideration of differing fuel degrade values. For instance, aircraft exhibiting consumption above 4% could be relegated to missions of short duration and/or training missions. This would mitigate the impact of the overconsumption. Aircraft performing at or below the 4% threshold should be judiciously employed on long-haul missions to affect a lesser overall fuel burn. Despite the inherent challenges with both the data and implementation of the analysis, there are substantial fleet-wide benefits to quantifying the tail-specific fuel degrade.

Future Work

One of the drawbacks of this study was the limited scope of the case study. Harnessing data from a single aircraft alongside only five additional samples from a second aircraft severely limited the extent to which inferences could be drawn about the C-5M in general. Clearly, the next step is to gather more MFOQA data on several different aircraft. The methodology employed in this study could then be applied to determine how these aircraft are consuming fuel. The confidence interval approach shown in Chapter IV is still valid and the question of interest is whether or not the CIs on the test aircraft's engines contain the 4% value. Departures from the 4% value (either above or below) would signal the need for a refined fuel "pad". Aircraft operating below 4% should have their degrade factors lowered and ramp fuel loads reduced. Aircraft operating above 4% should have their degrade factors raised and ramp fuel loads increased. Degrade factors above 4% could also alert maintenance personnel to possible malfunctions. After enough time that a large sample size is gathered, AMC may even reconsider the "baseline" 4% value itself. If most aircraft are trending one direction or the other (either above or below 4%), then there would be evidence that the population fuel degrade value is something other than 4%.

In terms of the methodology itself, the use of the LOESS smoother upon MFOQA fuel flow readings culled from stable cruise subsets is not the only procedure available. The use of various regression algorithms such as those utilized by Srivastava (2012) could apply. Control functions such as Kalman or Weiner filters may also be useful in capturing the fuel flow readings while simultaneously reducing the autocorrelated noise. The various studies from Simon and others described in Chapter II offer a springboard for the use of such techniques upon MFOQA. Simulation techniques such as the Batched Means method described by Law (2007) are effective at reducing autocorrelation and could be effectively employed on the MFOQA fuel flow data. Any or all of these avenues could be explored in future studies aimed at quantifying tail specific fuel degrade values.

Recommendations for Action

Based on the outcomes of this study, it is recommended that AMC explore methods of utilizing MFOQA to obtain tail-specific fuel degrade values for the C-5M. Much of the groundwork is outlined in this study and the Lockheed (2014) study already briefed to AMC. The data is available and the cost savings potential is real.

Summary

This thesis outlined the use of MFOQA data to improve C-5M fuel efficiency. The first chapter explored the background of various issues surrounding the fueling and operation of aircraft fleets and outlined the cost savings potential of the project. The dataset itself is described and the applicable research outlined in Chapter II. Chapter III provides an in-depth discussion of the thesis methodology and the techniques used to translate MFOQA data into meaningful fuel degrade figures. The results of this study are outlined in Chapter IV and demonstrate the usefulness of MFOQA in quantifying the fuel consumption behavior of AMC’s C-5M aircraft. Although conducted as a case study, the results have fleet-wide implications for both fuel efficiency and maintenance operations. The analysis could be easily expanded to a greater number of aircraft which would yield further insights on the fuel consumption behavior of the fleet.

Appendix A: Algorithms

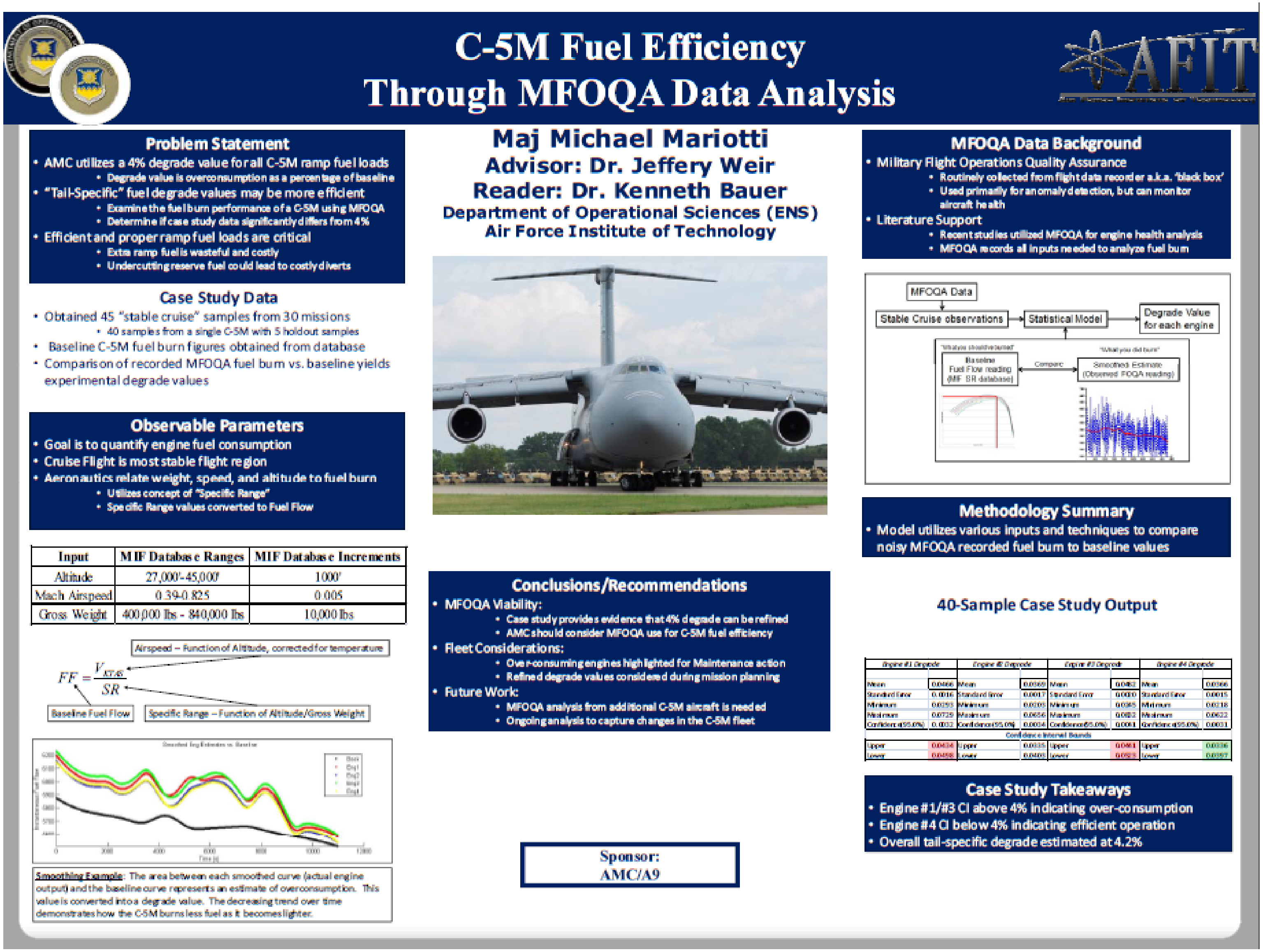
Algorithm 1 Estimate Fuel Degrade using MFOQA

```
Obtain MFOQA readings at 1 sample/sec
Parse MFOQA dataset into stable cruise segments
while 27,000' < Alt < 42,000' and Alt±25' do
   Record stable cruise segment if > 3600 records (1 hr)
   Trim first/last 5 min of cruise (300 records) to ensure level, stable flight
end while
Calculate baseline fuel burn
for all stable cruise segments do
   Interpolate Specific Range values using MFOQA inputs
   Convert each Specific Range value to an instantaneous Fuel Flow reading
   Integrate Fuel Flow readings over stable cruise flight time to obtain
   total baseline burn
end for
Calculate actual fuel burn
for all stable cruise segments do
   Smooth MFOQA-observed Fuel Flow to reduce noise {this study uses
   LOESS}
   Integrate Fuel Flow readings over stable cruise flight time to obtain
   total actual burn
end for
Calculate difference and percent degrade
for all stable cruise segments do
   Subtract baseline estimate from actual estimate to obtain
   "overconsumption" figure
   Divide overconsumption figure by baseline estimate to obtain
   "percent degrade" figure
end for
Aggregate output from each engine and each cruise segment to
estimate aircraft overall degrade
```

Algorithm 2 Compare CFP and MFOQA-observed Fuel Burn

```
Match stable cruise segments to CFP waypoints
for all stable cruise segments do
    Match MFOQA Gross Weight to CFP Waypoint using 'FLRM'
    Record first/last CFP Waypoint corresponding to MFOQA Gross Weight
end for
for all matching cruise segments do
    Match Lat/Long coordinates for each Waypoint in the span
    - CFP Waypoint coords in DD MM S format
    - MFOQA output in DD.nnnn format
    - Conversion: MM S/60 ≈ nnnn
    Calculate baseline fuel burn {Algorithm 1, steps 9-11}
    Calculate acutal fuel burn {Algorithm 1, steps 14-15}
end for
Compare outputs
- Model output for baseline and MFOQA-observed
- Difference in 'FLRM' for CFP
```

Appendix B: Quad Chart



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14. ABSTRACT
This study investigates the usage of Military Flight Operations Quality Assurance (MFOQA) data as a means to obtain precise, aircraft-specific fuel loads. Currently, USAF C-5M aircraft include a 4% "degrade" value in their fueling practices. MFOQA data are analyzed in an attempt to refine this value. Case study data are analyzed from a single C-5M. A model is constructed using smoothing techniques which compare MFOQA actual observations to a baseline flight test model. The resulting figures are applicable to fuel planning and fuel efficiency concepts. Validation is presented through comparison with computerized flight planning software output. Results from the case study analysis are presented within the framework of fleet-wide implementation and maintenance practices.

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